Denoising of Surveillance Video Using Adaptive Gaussian Mixture Model Based Segmentation Towards Effective Video Parameters Measurement

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***Abstract*—In recent times, capturization of video became more feasible with the advanced technologies in camera. Those videos get easily contaminated by noise due to the characteristics of image sensors. Surveillance sequences not only have static scenes but also dynamic scenes. Many efforts have been taken to reduce video noise. Averaging the frame as an image had limited denoising effect and resulted in blur. Such result will be avoided if we separate foreground and background, and make background to be averaged only. Recently, a number of video object segmentation algorithms have been discussed and unfortunately most existing segmentation algorithms are not adequate and robust enough to process noisy video sequences. Since the target video contains noise, a large area of background is incorrectly classified as moving objects and obvious segmentation error will appears. Therefore for robust separation, a segmentation algorithm based on Gaussian Mixture Models adaptive to light illuminations, shadow and white balance is proposed here. This segmentation algorithm processes the video with or without noise and sets up adaptive background models based on the characteristics of surveillance video to accomplish segmentation, reducing background noise by averaging and foreground noise by ML3D filter. The proposed method increased PSNR about 4.5 db compared to existing method and is capable of preserving video content. It is performed for two different video sequences.**

***Keywords*-noisy surveillance video, adaptive background models, segmentation, background denoising, foreground denoising, video parameters.**

I. Introduction

Video has largely turned into a necessary component of today's multimedia applications. Video surveillance is the heart of modern security systems .Because of the conditions of device and environment, surveillance video cannot get rid of noise. The presence of noise in a video sequence degrades both its visual quality, as well as, the effectiveness of subsequent processing tasks.

The classical image denoising algorithms which are used to reduce noise are divided into two categories: the first process every frame independently as still image [2].The other type makes use of correlation between adjacent frames to get better effect. Reference [3] extended 2D to 3D filter. All these algorithms are simple to implement but resulted in motion blurring and limited denoising capability. The proposed approach gives individual concentration on foreground and background of the noisy video to preserve the video information. Consequently, the next task is to segment the video showing background and foreground.

Several approaches have been proposed by researchers for video object segmentation [1]. A few methods are computationally expensive but provide in general, accurate results while others have low computation but fail to offer reliable segmentation. A principal disadvantage of most methods is that they are not tested on noisy videos and videos with artifacts.

The goal is to create a robust, adaptive segmentation system that is flexible enough to handle variations in lighting, moving scene clutter, multiple moving objects and other arbitrary changes to the observed scene. In this paper, a novel approach for segmentation of moving video objects in both noiseless and noisy colour video sequences towards effective video retrieval is proposed. To the video sequences corrupted with Gaussian noise, the results show that the new algorithm increases PSNR about 9 dB.

The rest of the paper is organized as follows: Part II presents the concept of adaptive Gaussian Mixture Model based segmentation. The algorithm for segmentation and selection procedure of filters for foreground and background is presented in Part III. The experimental results are given in Part IV. Finally, the last part brings out the conclusion and future research.

II. Adaptive Gaussian Mixture Modelling

Each pixel in a frame will be subjected to different environments. Normally if a background model is available, moving objects could be easily detected from the difference between each video frame and the background. While analysing the video acquisition noise, each surface pixel is distributed as a single Gaussian distribution model which changes with light alone. Adaptive Gaussian per pixel will satisfy the surfaces where light keeps on changing over time. In practice, multiple surfaces often appear in the view frustum of a particular pixel and the lighting conditions change. The background model should be adaptive so that manual reinitialisation will be avoided. Thus multimodal Gaussian distributions are necessary [4].We use a mixture of adaptive Gaussians to approximate this process. Each time the parameters of the Gaussians are updated, the Gaussians are evaluated using a simple logistic process to interpret which objects are likely to be the static and dynamic scenes.

III. Proposed Algorithm

A. Filter Selection Procedure for Surveillance Video

Presently, video cameras often use sensors called CCD (Charge Coupled Device) which includes noises like Gaussian and Poisson noise. Here the noise is assumed to be additive whose mean is zero. The image added with noise is expressed by the following equation.

$$Q=P+A,\ E(A)=0 \quad (1)$$

Where Q is the signal polluted with noise, P is the original signal and A is the noise whose mathematical expectation is zero. The expectation of Y is equal to:

$$E(Q) = E(P + A) = E(P) + E(A) = E(P) \quad (2)$$

If X is constant, then P = E (Q) since E (P) = E (Q).Therefore if the image sequence is static, estimation of original image can be obtained from averaging of noisy frames.

Video brings third dimension to a problem. The filters like median, wiener, ML3D (3D Multilevel Filter) are analysed and best filter is selected for foreground. ML3D [5] is used to reduce noise for dynamic sequences. It is a kind of 3D extended median filter and outperforms other similar filters.

B. Flow and Implementation of Adaptive GMM Segmentation and Denoising Algorithm

The overall flowchart of proposed denoising algorithm based on background modelling is as follows:

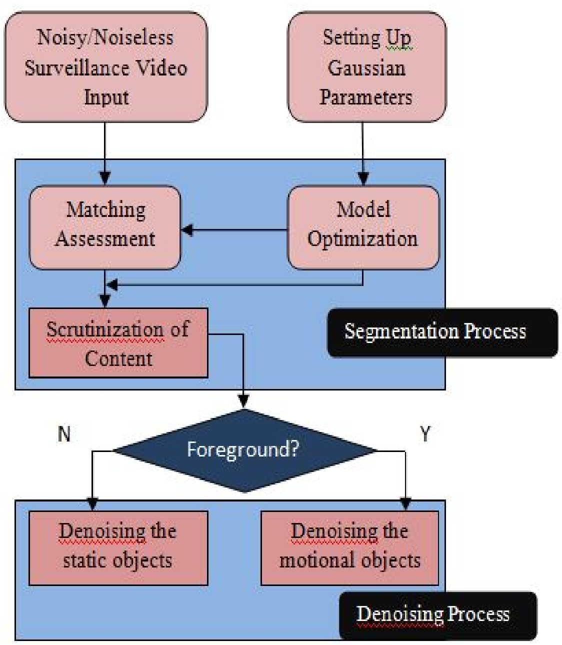


Fig. 1 Flowchart of GMM based denoising algorithm

1) *Properties of Video:* The number of file formats used in multimedia continues to proliferate. The length, width, frames per second, file format, number of frames is noted. The frames of the video are analysed. The pictorial representation of GMM segmentation is as follows:

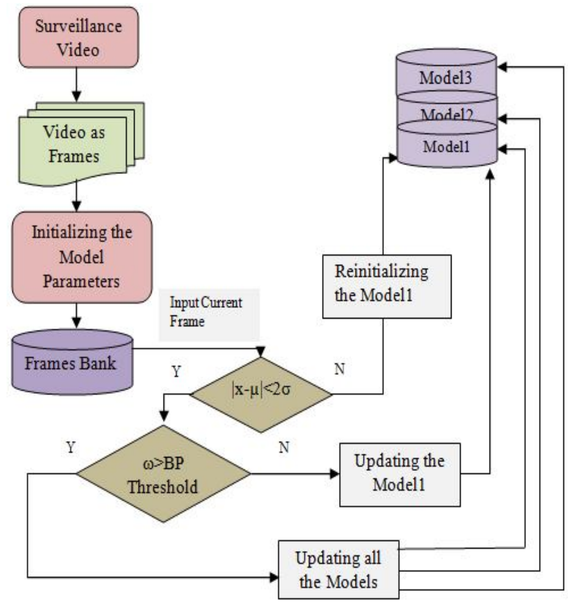


Fig. 2 Flowchart of GMM segmentation algorithm

2) *Model Declaration:* The Gaussian parameters mean μ_i, standard deviation σ_i, weight ω_i of each model are pre-declared to μ_{INIT}, σ_{INIT}, ω_i for 1/G .(i=l, 2,..... G) The value of μ_{INIT} significantly disturbs the primary sequence of the process. The value of σ_{INIT} is directly proportional to the updation rate .So σ should be selected as a moderate value in order to preserve the background and foreground separation.

3) *Matching Assessment*: Threshold for light variations like the objects which becomes static after a particular time, shadow, and light illumination is determined by experiments and a suitable value is chosen so that denoising effect does not get degraded.

4) *Model Reconfiguration:* Each pixel value X_t is compared with the prevailing K Gaussian distributions to figure out the matched and unmatched pixel.This is extremely useful when different regions have different lighting [6].Three cases are undertaken in model updation process. If the absolute value of the change in current pixel value with the mean is less than the twice of variance then those pixel values corresponds to background and then the weights are sorted in descending order .As a result, the least probable distribution will be at the bottom and the highest weight at the top.

$$\text{Diff} = \text{threshold} * \text{sigma} \quad (3)$$

where Diff is the absolute value of difference between current frame pixel value and mean of G model. Further to the execution of the equation the rate at which the reconfiguring matching values is determined and weight variance and sigma are changed accordingly. This change follows on three different classifications. On matching weights, variance and mean are modified for least weighed model. On unmatching the variance is restored with initial value, weight is multiplied with a factor of 0.5 and mean is changed with pixel of current frame. On a special case where matching value exceeding back ground proportion needs model optimization but at phased manner in order to do that weight, variance and mean are modified for all three GMM models. The parameters of the distribution are up- dated as shown in Equation (4-6).

$$\mu = (1-\rho)\mu + \rho x \tag{4}$$

$$\sigma = \sqrt{1-\rho\sigma^2 + \rho(x-\mu)^2} \tag{5}$$

The update factor varies according to the deviations in the matching judgement process. The update equations for the slight and deep variations cases are as follows:

$$\rho = e^{\frac{(x-\mu)^2\sigma}{(-2\sigma^2)(\sqrt{2\pi\sigma})}} \tag{6}$$

$$\rho = \beta * \frac{\alpha}{\sigma} \tag{7}$$

Where ρ **is** directly proportional to α and it has a major impact in the update speed of μ-σ.As the weight changes, ρ may become very large, even larger than 1, so it is necessary to set an upper limitation for ρ.One of the significant advantages of this method is that when something is allowed to become part of the background, it doesn't destroy the existing model of the background. Therefore, if an object is stationary just long enough to become part of the background and then it moves, the distribution describing the previous background still exists with the same μ and σ, but a lower ω and will be quickly re-incorporated into the background.

5) Scrutinization of Content: Based on the matching assessment, silhouette image is generated. Background proportion value help us in assisting the pixel whether it belongs to foreground and slighter variation in background. Background proportion threshold should be a trade-off value, on selection of higher value leads to delayed optimization of background model and lower value will fail to identify foreground.

6) *Denoising:* Based on the silhouette frame denoising is applied. In that frame by and large 60 to 70 percentage of the frame will be occupied by background and rest by foreground. In general for a movie the presence of background will be more so the application of average filter will be effective rather implementing for a foreground.

Filtering on dynamic objects require some more care since the noise gets polluted heavily on the motional objects.ML3D filter gives uniform effect on the overall frame but less effective when compared to average filter on static scenes. This filter is developed based on the preservation of different features in the first level of the multilevel structure. The first level consists of two 7-point median filters each preserving different features of the input image. The first level 7-point filters are

$$m_+ = MED\ \{D_1, E_1, F_1, B_1, H_1, E_0, E_2\} \tag{7}$$

$$m_X = MED\ \{A_1, C_1, E_1, G_1, I_1, E_0, E_2\} \tag{8}$$

and the final output is

$$y = MED\ \{m_+, m_X, E_1\} \tag{9}$$

So sharing two filters for a whole frame will lead to effective raise in PSNR on overall frame than by applying individually for the frame.

IV. EXPERIMENTAL RESULTS

This section presents the results obtained from the experimentation on the proposed segmentation based denoising algorithm. Initially, a surveillance video is taken where the moving objects becomes immovable after a particular period. The comparative analyses of filters are performed to select suitable filter for foreground and background. The video is applied for traditional approach of background subtraction. The conventional method failed to update the motions which keep on changing with the real world. The method presented here models the background by updating the frames constantly. The intermediate and final results obtained in segmenting the video objects in a colour video sequence are presented here. Denoising of foreground and background is done separately showing improved PSNR with other methods. The same is applied for noisy traffic surveillance video. Robust segmentation is achieved using Gaussian Mixture Model and traffic parameters are carried out at different environments where the traffic condition changes as well as the light illumination.

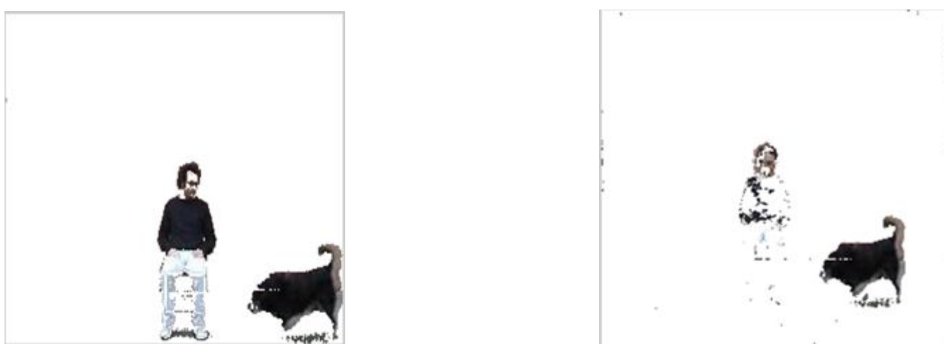
(a)Frame 112 (b) Frame 255 (c) Frame 450

Fig 3 Frames of color video sequences with Gaussian noise

(a)Frame 112 (b) Frame 255 (c) Frame 450

Fig 4 Grayscale converted Frames

Fig 5 Estimated Gaussian Mixture Background Modeled frames



(a) Conventional Method-Foreground (b) Proposed Method-Foreground

Fig. 6 Comparative analysis of Conventional and GMM Segmentation

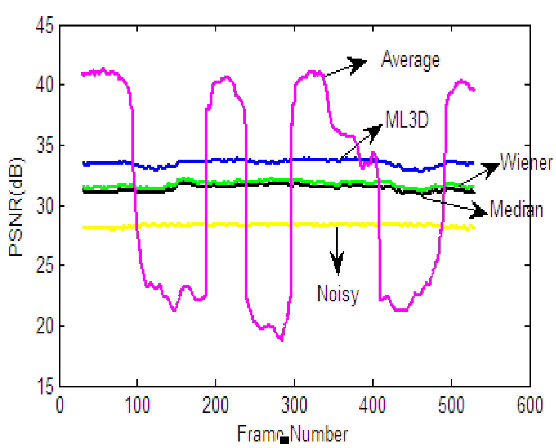


Fig 7 Filter selection analysis for foreground and background

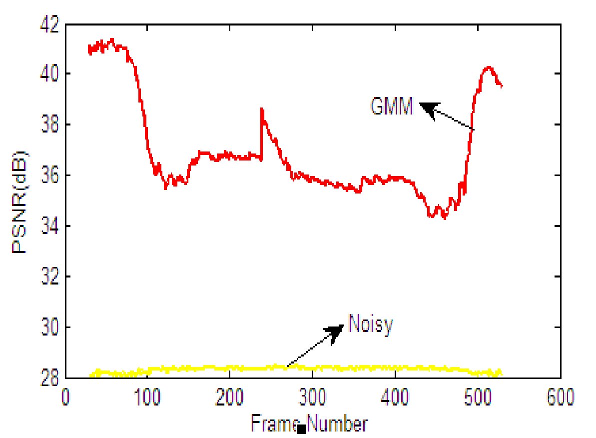


Fig 8 Improved PSNR curve for processing noisy sequence with GMM Based denoising algorithm

Fig 9 Noisy sequence

Fig 10 Denoised sequence using GMM Segmentation

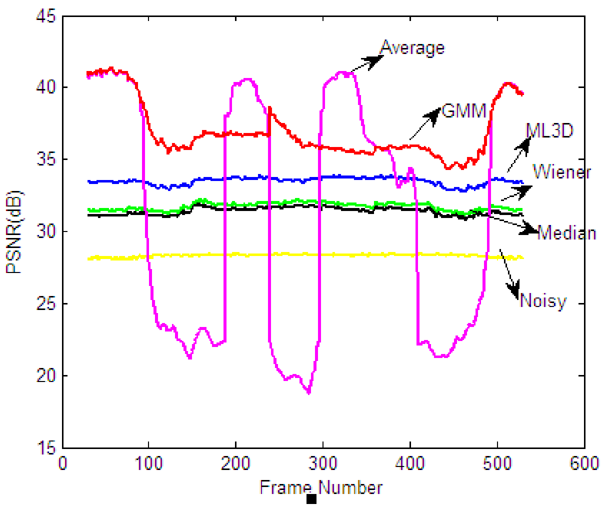


Fig 11 PSNR performance analysis of traditional and GMM algorithm

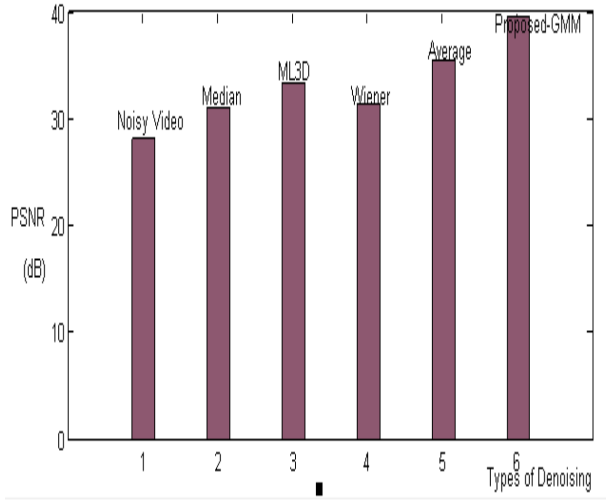
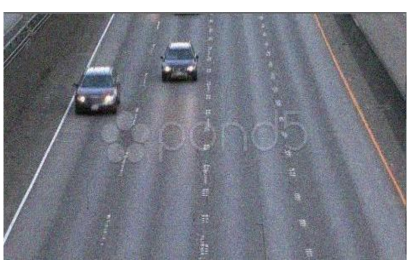


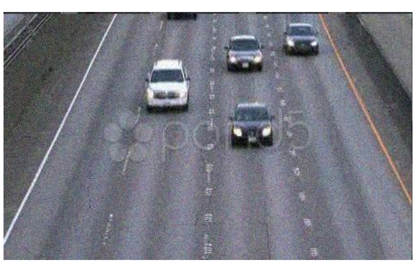
Fig 12 Improved PSNR bar graph for GMM based denoising algorithm

TABLE I
RESULTS OF PROCESSING OF NOISY SURVEILLANCE VIDEO SEQUENCE WITH DIFFERENT ALGORITHMS

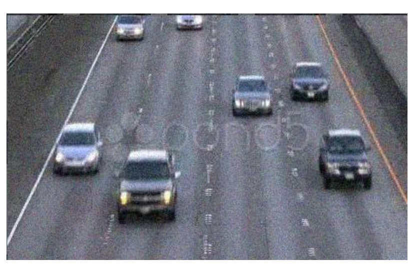
ALGORITHMS	**Gaussian noise, average PSNR is 28.25 dB**	
	Average PSNR(dB)	**Improvement(dB)**
1) MEDIAN	**31.51**	**3.26**
2) WIENER	**32.40**	**4.15**
3) ML3D	**33.40**	**5.15**
4) PROPOSED ALGORITHM	**37.99**	**9.74**



(a)Frame 25



(b) Frame 195

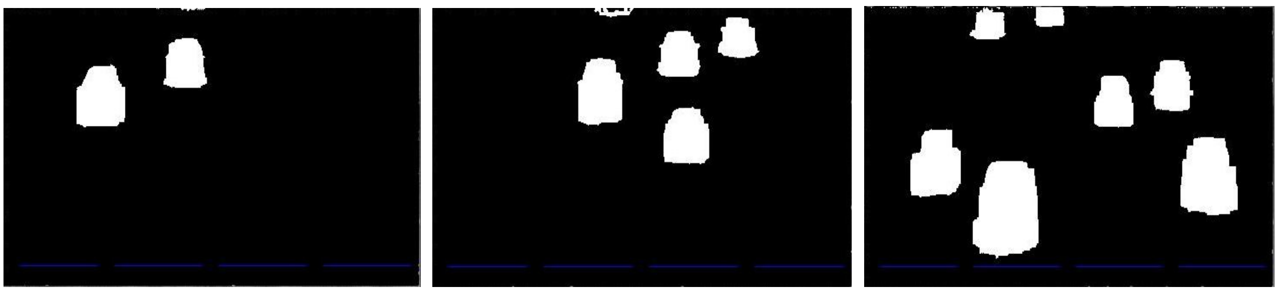


(c) Frame 269

Fig 13 Frames of traffic colour video sequences with Gaussian noise

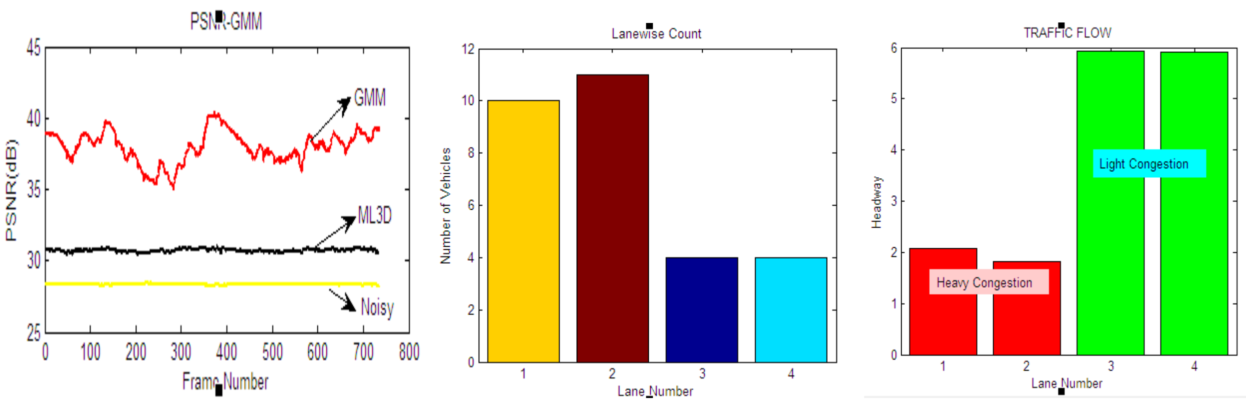
(a)Frame 25 (b) Frame 195 (c) Frame 269

Fig 14 Proposed Method (GMM) showing foreground segmentation



(a)Frame 25 (b) Frame 195 (c) Frame 269

Fig 15 GMM Segmented frames displaying the detection region to sense traffic quantities



(a) (b) (c)

Fig 16 (a) Improved PSNR curve for noisy traffic sequence (b) Counting results obtained for 4 lane traffic highway movie (c) Headway results showing the congestion performance

V. CONCLUSION AND FUTURE RESEARCH

Segmentation algorithm based on Gaussian Mixture Models is implemented to achieve robust segmentation for noiseless and noisy video sequences. The existing work achieved segmentation but failed to handle different environments. The proposed work possesses much greater robustness to problematic phenomena than the prior state-of-the-art, without sacrificing real-time performance, making it well-suited for a wide range of practical applications in video event detection and recognition. To the sequences of surveillance video polluted with Gaussian noise, the results show that the new algorithm increases PSNR effectively and maintains the visual quality to obtain clear information from the video. The work is extended for noisy traffic surveillance video and the important parameters such as traffic flow, time headway and traffic volume are computed for denoised video obtained using the proposed GMM based denoising algorithm. Future research is to enhance the system and improve the capability of noise reduction for variant types of scenes.

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